Transactive Energy and Flexibility Provision in Multi-microgrids using Stackelberg Game

Weiqi Hua, *Member, IEEE,* Hao Xiao, *Member, IEEE,* Wei Pei, *Member, IEEE,* Wei-Yu Chiu, *Member, IEEE,* Jing Jiang, *Member, IEEE,* Hongjian Sun, *Senior Member, IEEE* and Peter Matthews

***Abstract*—Aggregating the demand side flexibility is essential to complementing the inflexible and variable renewable energy supply in achieving low carbon energy systems. Sources of demand side flexibility, e.g., dispatchable generators, storages, and flexible loads, can be structured in a form of microgrids and collectively provided to utility grids through transactive energy in local energy markets. This paper proposes a framework of local energy markets to manage the transactive energy and facilitate the flexibility provision. The distribution system operator aims to achieve local energy balance by scheduling the operation of multi-microgrids and determining the imbalance prices. Multiple microgrid traders aim to maximise profits for their prosumers through dispatching flexibility sources and participating in localised energy trading. The decision making and interactions between a distribution system operator and multiple microgrid traders are formulated as the Stackelberg game-theoretic problem. Case studies using the IEEE 69-bus distribution system demonstrate the effectiveness of the developed model in terms of facilitating the local energy balance and reducing the dependency on the utility grids.**

***Index Terms*—demand side flexibility, game theory, multi-microgrid, prosumer, smart grid, transactive energy.**

I. Introduction

CONVENTIONAL electricity systems are vertically integrated architecture in which the electricity generation, transmission, and distribution are managed by centralised authorities [1]. The deregulation of electricity systems enables the transition towards liberalised electricity markets [2]. In the liberalised electricity markets, such as the Great Britain (GB) electricity market [3], electricity generation and supply are decoupled, resulting in the competitive wholesale markets and retail markets. Multiple suppliers buy electricity from generators in the wholesale markets in order to satisfy the electricity demand of their consumers in the retail markets. The operation of power grids is distinct from the generation, leading to independent transmission system operators (TSOs) and distribution system operators (DSOs) [4].

W. Hua is with the School of Engineering, Cardiff University, Cardiff CF24 3AA, UK (e-mail: huaw5@cardiff.ac.uk).

H. Xiao (corresponding author) and W. Pei are with the Institute of Electrical Engineering, Chinese Academy of Sciences, Beijing 100190, China (e-mail: {xiaohao09, peiwei}@mail.iee.ac.cn).

W.-Y. Chiu is with the MOCaRL Lab, Department of Electrical Engineering, National Tsing Hua University, Hsinchu 300044, Taiwan (e-mail: chiuweiyu@gmail.com).

J. Jiang is with the Department of Mathematics, Physics and Electrical Engineering, University of Northumbria, Newcastle, NE1 8ST, UK (e-mail: jing.jiang@northumbria.ac.uk).

H. Sun and P. Matthews are with the Department of Engineering, Durham University, Durham, DH1 3LE, UK (e-mail: {hongjian.sun, p.c.matthews}@durham.ac.uk).

Regulations for decarbonising power systems support the integration of distributed renewable energy sources (DRESs), such as the roof-top solar panel. Conventional consumers are able to actively produce, consume, and store energy using these DRESs, advanced information and communication technologies, and storage devices, giving them a new role of prosumers [5]. In local energy markets, prosumers are able to exchange electricity between each other and provide flexibility to the utility grids, which brings additional revenues to prosumers [6], improves local energy balance [7], and reduces the needs for reinforcing power system infrastructures [8]. Nonetheless, accommodating the role of prosumers requires flexible architectures of local energy markets.

Microgrids, as a self-sufficient energy system interconnecting to distribution networks [9], [10], provide a solution to the reliable integration of prosumers. The innovation of transactive energy [11] in local electricity markets enables prosumers to exchange both energy and capital between each other within the same geographical region. To facilitate the commercial relations between microgrids and local energy markets, a virtual entity, microgrid trader [12], was designed to manage the resources dispatch and energy trading for a microgrid. As a neutral facilitator, the microgrid trader encourages and aggregates the demand side flexibility from dispatchable generators, storage devices, and flexible loads [13] of its prosumers. These sources of demand side flexibility can be aggregated and subsequently provided to the utility grids for complementing the inflexible and variable renewable energy sources on the generation side.

Managing the transactive energy and providing flexibility from distribution networks have been well documented in the literature. Typical approaches for managing the operations of power systems and energy markets, e.g., energy dispatch, demand side management, state estimation, and energy trading, include the optimisation [14], [15], agent-based model [16], [17], game theory [18]–[24], or combination of these approaches. The optimisation approach assists the stakeholders in power systems or energy markets to find optimal decisions in achieving certain targets, e.g., operational profits maximisation and power losses minimisation. Marzband *et al.* [14] proposed a smart transactive energy framework to dispatch flexibility sources and allocate profits among microgrids using the developed optimisation approach, through which microgrids formed a coalition to improve their competitiveness. Wang *et al.* [15] designed a bi-level optimisation framework to coordinate the transactive energy of microgrids with the operation of distribution systems. The agent-based model simulates the actions and interactions of stakeholders in power systems or energy markets, in order to analyse the behaviours of these stakeholders and corresponding impacts on the whole systems. Nunna and Srinivasan [16] proposed an agent-based approach for managing the transactive energy, through which the surplus energy supply or residual energy demand could be traded in a transactive market. As flexibility sources, the flexible demand and storage systems in microgrids were incorporated into the operation of power systems to address the energy imbalance. Janko and Johnson [17] developed a general multi-agent method to assist the energy trading between microgrids when they connect to the utility grids, for the purpose of reducing the operational costs of microgrids.

Game-theoretic approaches have drawn increasing attention for analysing the decision making and interactions of stakeholders in local energy markets. The cooperative game enables every stakeholder to gain benefits through participating the game rather than acting independently [25]. Du *et al.* [18] implemented a cooperative game-theoretic approach to model the coordination among multiple microgrids in distribution networks through forming one grand coalition. To improve the reliability and operational efficiency of distribution networks, researchers in [19] developed a coalitional game to incentivise the localised energy transaction of microgrids. With respect to the non-cooperative game, each stakeholder seeks to maximise its own benefits and all stakeholders would reach an equilibrium outcome, at which no stakeholder wants to deviate [26]. In [20], generators, consumers, and retailers were modelled as players by a non-cooperative game approach to analyse interactions between distribution networks and microgrids. Fu *et al.* [21] formulated a bi-level optimisation problem using the non-cooperative game, by which the hybrid AC/DC distribution network was at the higher level to control power flows and multiple microgrids were at the lower level to manage the energy storage systems. The Stackelberg game-theoretic model features a sequential decision-making problem [22]. A leader at a higher level initially determines its strategies. Followers at the lower level subsequently formulate their responding strategies. Liu *et al.* [23] implemented the Stackelberg game to manage the energy sharing considering the stakeholders of microgrid operator at the leader level and prosumers at the follower level. In [24], a framework for power system scheduling was designed using the Stackelberg game theory to facilitate the penetration of renewable generation and carbon reduction in energy consumption.

In the context of our proposed research, the DSO announces the required flexibility prioritising the dispatch and responses of multiple microgrid traders, in order to achieve the target of local energy balance for the DSO and profit maximisation for individual microgrid traders and their prosumers. The Stackelberg game-theoretic approach can precisely capture this sequential action process. For this reason, our research modelled the decision making and interactions between the DSO and multiple microgrid traders as a Stackelberg game.

Although extensive studies have been conducted, there exist three primary research gaps as follows.

- Designing a structure of the local energy market to align the interests of individual prosumers, e.g., their generating profits, with the benefits of power systems, e.g., flexible operation and local energy balance, is necessary, but missing in the literature.
- How the DSO exploits the market innovation of transactive energy to facilitate the flexibility provision from prosumers has not been investigated.
- When multiple microgrids in the same distribution network exchange energy with each other, a pricing and clearing mechanism needs to be designed.

By addressing these research gaps, this paper offers the following contributions:

- A novel structure of local energy market is designed to manage the transactive energy and facilitate the flexibility provision from prosumers in microgrids.
- How the DSO facilitates the flexibility provision through the transactive energy among multiple microgrid traders is analysed by a Stackelberg game-theoretic model. The DSO seeks for local energy balance by scheduling the operation of microgrids and determining the imbalance prices, and individual microgrid traders seek for maximising the profits of their prosumers through dispatching flexibility sources and energy trading.
- Case studies testify the benefits of the developed model in terms of facilitating the transactive energy and flexibility provision of microgrids, achieving the local energy balance, and reducing the dependency on the utility grids.

The rest of this paper is organised as follows. Section II formulates the framework of local energy markets by analysing the objectives and decisions of the DSO and multiple microgrid traders. The interactions between these stakeholders are modelled as the Stackelberg game-theoretic problem in Section III. The results of case studies to show the effectiveness of the designed framework are provided in Section IV, and Section V draws the conclusion and discusses future works.

II. Framework of Local Energy Markets

Fig. 1 shows the strategical decision making and interactions between the DSO and multiple microgrid traders. The DSO aims to achieve local energy balance through scheduling the operation of multi-microgrid and determining imbalance prices. Each microgrid trader aims to maximise profits for its ensemble of prosumers through aggregating surplus flexibility sources from its prosumers and participating in the transactive energy to trade with other microgrid traders. This research focuses on the day-ahead electricity markets.

Fig. 2 presents the relationship between power systems and local energy markets. A group of geographically connected prosumers (denoted by dots) forms a microgrid. The prosumers include residential, commercial, and industrial consumers who are able to produce energy on-site. Meanwhile, individual prosumers own their flexibility sources including dispatchable generators, electric vehicles, storage systems, and flexible loads. First, prosumers belonging to the same microgrid can share their flexibility sources with each other at agreed prices. Second, after internal energy sharing among prosumers, a microgrid trader helps its prosumers aggregate the surplus energy supply or demand, and exchange with other microgrids. A microgrid can either connect to the utility grids or

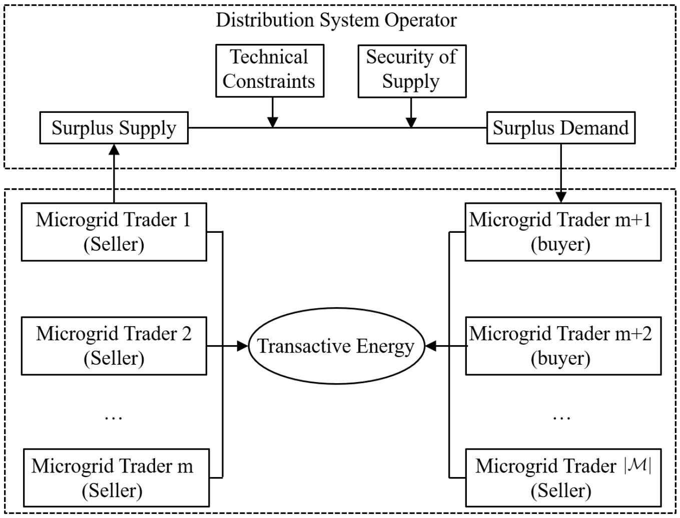

Fig. 1. Strategical decision making and interactions between the distribution system operator and microgrid traders.

disconnect and operate independently in an islanded mode [27]. In the context of our research, only the connected mode is considered for the purpose of flexibility provision to the distribution networks or transmission networks.

Remark: From the power system level, if a microgrid still has surplus supply/demand after the transactive energy, this surplus energy can be either exported/imported to/from the utility grids, or curtailed/unsatisfied. From the prosumer level, they negotiate the prices of energy sharing between each other under predefined auction mechanisms. Both the power system level and prosumer level are beyond the scope of this research, since this research focuses on the roles and relationship between the DSO and microgrid traders.

Let $\mathcal{N}$ represent the set of buses, i.e., prosumers, within a microgrid, indexed by $n \in \mathcal{N}$, and $\mathcal{M}$ represent the set of microgrids, indexed by $m \in \mathcal{M}$. The total numbers of buses and microgrids are denoted by $|\mathcal{N}|$ and $|\mathcal{M}|$, respectively.

A. The Role of Microgrid Trader

A microgrid trader seeks to maximise the profits for its prosumers through providing three functions: *1)* helping its sellers and buyers within the same microgrid match with each other, *2)* helping the DSO balance local energy by facilitating the flexibility sources, and *3)* aggregating surplus generation or consumption to trade with other microgrids. First, the costs of operating flexibility sources by individual prosumers are modelled as follows:

• Dispatchable generators: The operational costs of a dispatchable generator can be modelled as follows [28]:

$$c_{\mathrm{DG},n,t} = \alpha_{\mathrm{DG},n} \cdot (p_{\mathrm{DG},n,t})^2 + \beta_{\mathrm{DG},n} \cdot p_{\mathrm{DG},n,t} + \gamma_{\mathrm{DG},n}, \quad (1)$$

where $c_{\mathrm{DG},n,t}$ is the operational costs of a dispatchable generator connected to the bus n at the scheduling time t, $p_{\mathrm{DG},n,t}$ is the power output of a dispatchable generator connected to the bus n at the scheduling time t, and $\alpha_{\mathrm{DG},n}$, $\beta_{\mathrm{DG},n}$, and $\gamma_{\mathrm{DG},n}$ are the cost coefficients of a dispatchable generator connected to the bus n. The operation of a dispatchable generator is subject to the power output constraint as

$$p_{\mathrm{DG},n,t} \leq p_{\mathrm{DG},n}^{\max}, \quad (2)$$

where $p_{\mathrm{DG},n}^{\max}$ is the maximum power output of a dispatchable generator connected to the bus n.

• Electric vehicles: A prosumer who owns an electric vehicle is able to sell the electricity to the power grids when the electric vehicle is inactive. The costs of the vehicle-to-grid can be modelled as follows according to [28]:

$$c_{\mathrm{EV},n,t} = \alpha_{\mathrm{EV},n} \cdot (p_{\mathrm{EV},n,t})^2 + \beta_{\mathrm{EV},n} \cdot p_{\mathrm{EV},n,t} + \gamma_{\mathrm{EV},n}, \quad (3)$$

where $c_{\mathrm{EV},n,t}$ is the costs of the vehicle-to-grid connected to the bus n at the scheduling time t, $p_{\mathrm{EV},n,t}$ is the power exported from the electric vehicle to the bus n at the scheduling time t, and $\alpha_{\mathrm{EV},n}$, $\beta_{\mathrm{EV},n}$, and $\gamma_{\mathrm{EV},n}$ are the cost coefficients of the vehicle-to-grid connected to the bus n. Considering the capacity limit of power grids, the constraint of maximum power exported from an electric vehicle holds as

$$p_{\mathrm{EV},n,t} \leq p_{\mathrm{EV},n}^{\max}, \quad (4)$$

where $p_{\mathrm{EV},n}^{\max}$ is the maximum power exported from an electric vehicle connected to the bus n.

• Storage system: Let $e_{\mathrm{S},n,t}$ denote the state of charge of a storage system of the bus n at the scheduling time t, and $\Delta p_{\mathrm{S},n,t}$ denote the charging or discharging rate of the storage system of the bus n at the scheduling time t. The positive value of $\Delta p_{\mathrm{S},n,t}$ indicates the power is charged to the storage system, and the negative value of $\Delta p_{\mathrm{S},n,t}$ indicates the power is discharged from the storage system. We have

$$\Delta p_{\mathrm{S},n,t} \cdot \Delta t = e_{\mathrm{S},n,t} - e_{\mathrm{S},n,t-1}, \quad (5)$$

where Δt is the scheduling interval.

The state of charge should be restricted by the capacity limit as

$$0 \leq e_{\mathrm{S},n,t} \leq e_{\mathrm{S}}^{\max}, \quad (6)$$

where $e_{\mathrm{S}}^{\max}$ is the maximum storage capacity.

The charging or discharging rate of the storage system should be limited by the maximum value as

$$|\Delta p_{\mathrm{S},n,t}| \leq \Delta p_{\mathrm{S}}^{\max}, \quad (7)$$

where $\Delta p_{\mathrm{S}}^{\max}$ is the maximum charge or discharge rate.

• Demand side management: The approaches of the demand side management in the context of this research include the load shifting and load curtailment. The load shifting aims to schedule the consumption period of the shiftable loads while remaining total consumption during the scheduling horizon unchanged, in responding to dynamic retail electricity pricing signals [29]. The load curtailment reduces the total consumption level of curtailable loads [30]. Both the load shifting and load curtailment would cause inconvenience for electricity consumers, which can be described by the disutility function [28] in a monetary manner as:

$$c_{\mathrm{DSM},n,t} = \alpha_{\mathrm{DSM},n} \cdot (\Delta d_{n,t})^2 + \beta_{\mathrm{DSM},n} \cdot \Delta d_{n,t} + \gamma_{\mathrm{DSM},n}, \quad (8)$$

where $c_{\mathrm{DSM},n,t}$ is the costs of demand side management in the bus n at the scheduling time t, $\Delta d_{n,t}$ is the shifted or

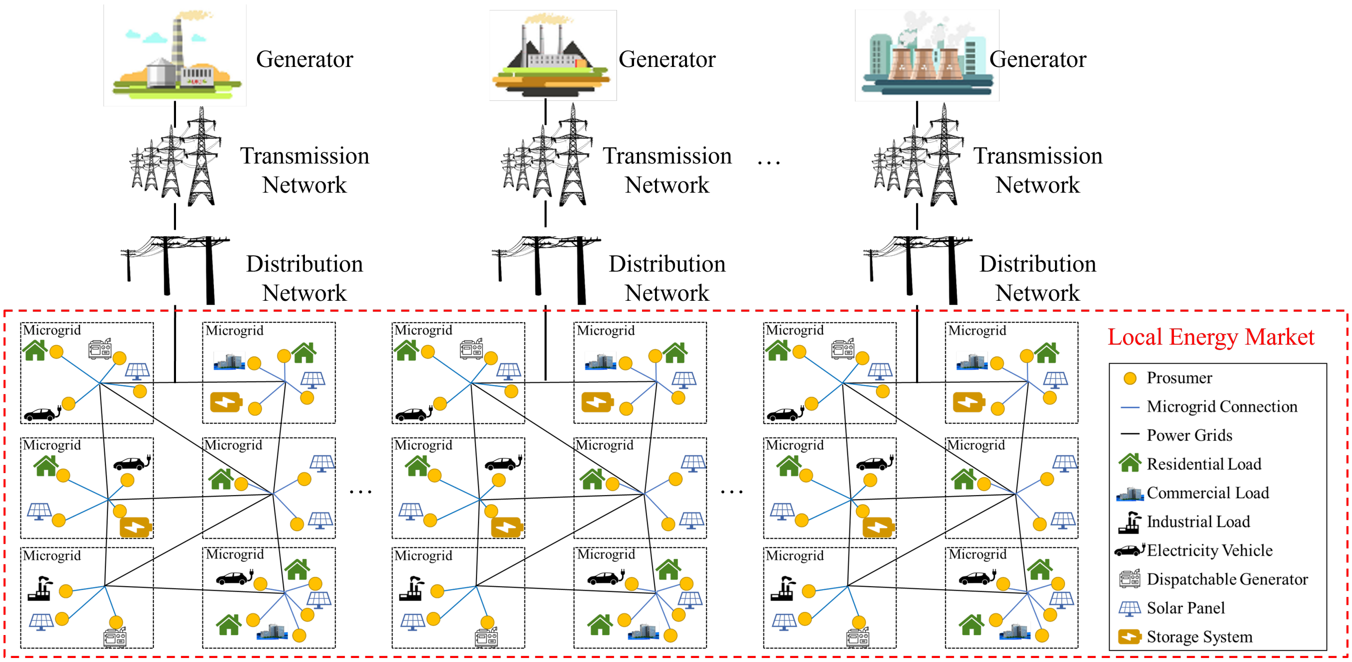

Fig. 2. Schematic illustration of the relation between power systems and local energy markets.

curtailed consumption in the bus n at the scheduling time t, and $\alpha_{\text{DSM},n}$, $\beta_{\text{DSM},n}$, and $\gamma_{\text{DSM},n}$ are the cost coefficients of the demand side management in the bus n.

For the load curtailment, we have

$$\sum_{t\in\mathcal{T}} \Delta d_{n,t}\cdot \Delta t > 0 \tag{9}$$

For the load shifting, we have

$$\sum_{t\in\mathcal{T}} \Delta d_{n,t}\cdot \Delta t = 0, \tag{10}$$

where $\mathcal{T}$ is the scheduling horizon. For the time interval of 0.5 h, we have (Δt, $|\mathcal{T}|$) = (0.5, 48).

Next, a microgrid trader aggregates the flexible power to meet local demand of its prosumers. The aggregate flexible power can be described as

$$p_{\text{FL},m,t} = \sum_{n\in\mathcal{N}} p_{\text{DG},n,t} + p_{\text{EV},n,t} - \Delta p_{\text{S},n,t} + \Delta d_{n,t}, \tag{11}$$

where $p_{\text{FL},m,t}$ is the aggregated flexible power of the microgrid m at the scheduling time t.

Let $p_{n,t}$ denote the power generation from non-dispatchable sources, e.g., solar, of the bus n at the scheduling time t, and $d_{n,t}$ denote the power demand of the bus n at the scheduling time t. The net power of a microgrid after meeting the local demand of its prosumers can be described as

$$p_{\text{NET},m,t} = p_{\text{FL},m,t} + \sum_{n\in\mathcal{N}} \left(p_{n,t} - d_{n,t}\right), \tag{12}$$

where $p_{\text{NET},m,t}$ is the net power of the microgrid m at the scheduling time t after meeting the local demand of its prosumers. A positive value of $p_{\text{NET},m,t}$ indicates that the microgrid m has the surplus power to be sold to other microgrids as an electricity seller; A negative value of $p_{\text{NET},m,t}$ indicates that the microgrid m has the surplus demand to be met by other microgrids as an electricity buyer.

The profits of a microgrid are the difference between the revenues and costs of the flexibility provision, which can be described as

$$\begin{aligned} f_{\text{p},m} = \sum_{t\in\mathcal{T}} \Big[& p_{\text{NET},m,t}\cdot \pi_{\text{FL},m,t}, \\ & - \sum_{n\in\mathcal{N}} \left(c_{\text{DG},n,t} + c_{\text{EV},n,t} + c_{\text{DSM},n,t}\right)\Big] \cdot \Delta t, \end{aligned} \tag{13}$$

where $f_{\text{p},m}$ is the objective function of profits of the microgrid m, and $\pi_{\text{FL},m,t}$ is the selling price (when $p_{\text{NET},m,t} > 0$) or buying price (when $p_{\text{NET},m,t} < 0$) of the microgrid trader m at the scheduling time t.

If all microgrids in the distribution network still have surplus supply, they can sell this surplus supply to the DSO at a price lower than the selling prices between microgrids. This lower price is defined as the system sell price (SSP). If all microgrids in distribution networks still have surplus demand, they can buy this surplus demand from the DSO at a price higher than the buying prices between microgrids. This higher price is defined as the system buy price (SBP). Both the SSP and SBP determined by the DSO are belong to the imbalance prices [31]. Hence, the selling or buying prices between microgrids are not lower than the SSP and not higher than the SBP as shown in Eq. (14). Otherwise, a microgrid would prefer to exchange with the DSO, driven by the objective of profit maximisation.

$$\pi_{\text{DSSP},t} \leq \pi_{\text{FL},m,t} \leq \pi_{\text{DSBP},t}, \tag{14}$$

where $\pi_{\text{DSSP},t}$ is the SSP at the scheduling time t, and $\pi_{\text{DSBP},t}$ is the SBP at the scheduling time t.

Therefore, the problem profit maximisation of a microgrid through the flexibility provision and energy trading can be described as

$$\max_{p_{\mathrm{DG},n,t}, p_{\mathrm{EV},n,t}, \Delta p_{\mathrm{S},n,t}, \Delta d_{n,t}, \pi_{\mathrm{FL},m,t}} f_{\mathrm{p},m}, \tag{15}$$

s.t.
(2), (4), (5), (6), (7), (9), (10), (11), (12), and (14).

B. The Role of Distribution System Operator

The DSO aims to achieve local energy balance through scheduling the operation of microgrids and determining the imbalance prices. First, the net power of the distribution network can be described as

$$f_{\mathrm{B}} = \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} p_{\mathrm{NET},m,t}, \tag{16}$$

where f_{B} is the objective function of local energy balance of the distribution network.

The DSO also maintains system constraints including the electric power balance, line flow constraints, apparent power constraints, voltage constraints, voltage angle constraints, and thermal power constraints as in [32].

Next, the DSO determines the imbalance prices to trade surplus supply or demand with microgrid traders. The imbalance prices are a linear function of the aggregated net power of all microgrids as

$$\begin{cases} \pi_{\mathrm{DSSP},t} = \varepsilon \sum_{m \in \mathcal{M}} p_{\mathrm{NET},m,t}, & \text{if} \sum_{m \in \mathcal{M}} p_{\mathrm{NET},m,t} > 0, \\ \pi_{\mathrm{DSBP},t} = \varepsilon \sum_{m \in \mathcal{M}} p_{\mathrm{NET},m,t}, & \text{if} \sum_{m \in \mathcal{M}} p_{\mathrm{NET},m,t} < 0, \end{cases} \tag{17}$$

where ε is the coefficient of imbalance price.

Therefore, the problem of achieving local energy balance of the DSO can be described as

$$\min_{p_{\mathrm{NET},m,t}, \pi_{\mathrm{DSSP},t}, \pi_{\mathrm{DSBP},t}} |f_{\mathrm{B}}|, \tag{18}$$

s.t.
(17).

III. Stackelberg Game-Theoretic Approach

This section introduces the proposed Stackelberg game-theoretic problem for modelling the interactions between the DSO and its multiple microgrid traders. A solution to the game-theoretic problem is subsequently developed based on the artificial immune system.

A. Problem Formulation

The interactions between a DSO and multiple microgrid traders are formulated as a Stackelberg game-theoretic problem, by which the DSO is at the leader level with strategies of the operational scheduling for microgrids and imbalance prices, $|\mathcal{M}|$ microgrid traders are at the follower level with strategies of dispatching flexibility sources and energy trading as responses. The procedures of the Stackelberg game between the DSO and $|\mathcal{M}|$ microgrid traders are described as follows:

Step 1: The DSO publishes the required flexibility, denoted as $\sum_{m \in \mathcal{M}} p^{\star}_{\mathrm{NET},m,t}$ by solving its optimisation problem based on the predicted generation and consumption.

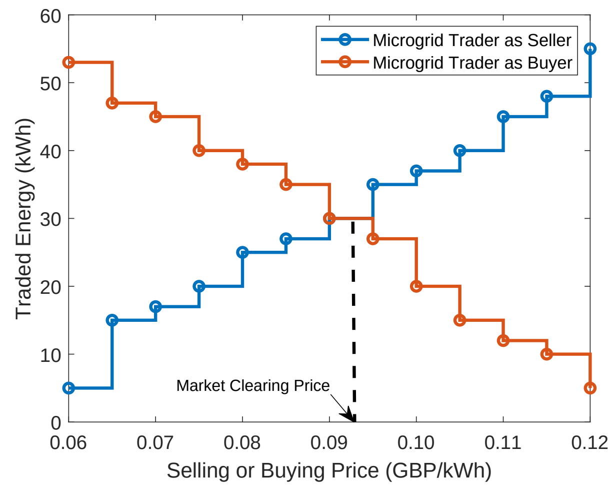

Fig. 3. Schematic illustration of how to determine the market clearing price for multiple microgrid traders through generating the curves of the aggregated supply and demand. The selling prices are arranged in the ascending order. The buying prices are arranged in the descending order.

Step 2: Receiving the information of required flexibility from the DSO, each microgrid trader decides its responding strategies of dispatching flexibility sources for individual prosumers, through solving its optimisation problem. The optimal decisions of dispatching flexibility sources are denoted as $\{p^{\star}_{\mathrm{DG},n,t}, p^{\star}_{\mathrm{EV},n,t}, \Delta p^{\star}_{\mathrm{S},n,t}, \Delta d^{\star}_{n,t}\}, \forall n \in \mathcal{N}$.

Step 3: Multiple microgrid traders help their prosumers trade aggregated surplus supply or demand $p^{\star}_{\mathrm{NET},m,t}$ at the optimal selling or buying prices, denoted as $\pi^{\star}_{\mathrm{FL},m,t}$, yielded by solving their own optimisation problems. The auction of microgrid traders is proceeded by the double auction mechanism [33]. The selling prices are arranged in the ascending order and the buying prices are arranged in the descending order, to generate the aggregated supply and demand curves. An example of the aggregated supply and demand curves is shown in Fig. 3. The market clearing price of multiple microgrid traders is the intersection point of two curves. The microgrid traders negotiate with each other by adjusting their selling or buying prices as shown in Eq. (19), until all unmatched supply or demand has been cleared, at which the Stackelberg equilibrium is reached.

$$\begin{cases} \pi'_{\mathrm{FL},m,t} = \pi_{\mathrm{FL},m,t} - \Delta\pi_{\mathrm{FL},m,t} & \text{if } p_{\mathrm{NET},m,t} > 0, \\ \pi'_{\mathrm{FL},m,t} = \pi_{\mathrm{FL},m,t} + \Delta\pi_{\mathrm{FL},m,t} & \text{if } p_{\mathrm{NET},m,t} < 0, \end{cases} \tag{19}$$

where $\pi'_{\mathrm{FL},m,t}$ is the new selling or buying price of the microgrid trader m at the scheduling time t after the adjustment, and $\Delta\pi_{\mathrm{FL},m,t}$ is the adjusted amount of the selling or buying price of the microgrid trader m at the scheduling time t.

Step 4: The DSO aggregates the surplus demand or supply of all microgrid traders, and determines the imbalance prices, denoted as $\pi^{\star}_{\mathrm{DSSP},t}$ or $\pi^{\star}_{\mathrm{DSBP},t}$, according to Eq. (17).

The flowchart of the procedures for the proposed Stackelberg game-theoretic problem is shown in Fig. 4.

B. Solution

To solve the Stackelberg game-theoretic problem, this research develops an artificial immune algorithm as proposed

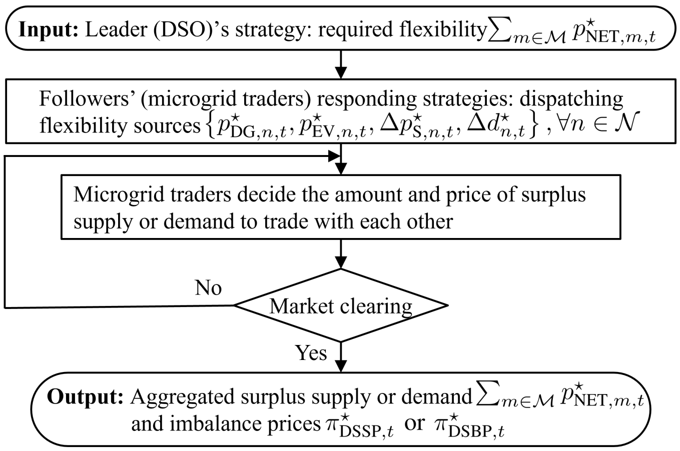

Fig. 4. Flowchart of the procedures for the Stackelberg game-theoretic problem between the leader (distribution system operator) and followers (microgrid traders).

by [34]. This algorithm is able to search the entire feasible spaces for decision variables, in order to find the global optimal solutions. To illustrate the proposed algorithm, first, decision variables and objective functions of the formulated optimisation problems are defined as:

$$\mathbf{p}_{\mathrm{F}}=\left[p_{\mathrm{DG},n,t}, p_{\mathrm{EV},n,t}, \Delta p_{\mathrm{S},n,t}, \Delta d_{n,t}, \pi_{\mathrm{FL},m,t}\right], \forall m\in\mathcal{M}, n\in\mathcal{N}, \tag{20}$$

$$\mathbf{p}_{\mathrm{L}}=\left[p_{\mathrm{NET},m,t}, \pi_{\mathrm{DSSP},t}, \pi_{\mathrm{DSBP},t}\right], \forall m\in\mathcal{M}, \tag{21}$$

$$\mathbf{f}_{\mathrm{F}}=\left[-f_{\mathrm{p},m}\right], \forall m\in\mathcal{M}, \tag{22}$$

$$\mathbf{f}_{\mathrm{L}}=\left[|f_{\mathrm{B}}|\right], \tag{23}$$

where $\mathbf{p}_{\mathrm{F}}$ is the vector containing the decision variables a follower, $\mathbf{p}_{\mathrm{L}}$ is the vector containing the decision variables from the leader, $\mathbf{f}_{\mathrm{F}}$ is the vector representing the objective function of a follower, and $\mathbf{f}_{\mathrm{L}}$ is the vector representing the objective function of the leader. In addition, the minimum and maximum constraints of a follower are denoted by $\underline{\mathbf{p}}_{\mathrm{F}}$ and $\overline{\mathbf{p}}_{\mathrm{F}}$, respectively. The minimum and maximum constraints of a leader are denoted by $\underline{\mathbf{p}}_{\mathrm{L}}$ and $\overline{\mathbf{p}}_{\mathrm{L}}$, respectively.

Key concepts with respect to the artificial immune system [35] are introduced as follows:

• *Concept 1 (Antigen and Antibody)*: A vector which is randomly generated from the feasible space of a decision variable, i.e., $\left[\underline{\mathbf{p}}, \overline{\mathbf{p}}\right]$, is defined as an antigen, denoted as $\mathbf{p}$. The value of objective function of this antigen is defined as an antibody, denoted as $\mathbf{f}(\mathbf{p})$. A group of generated antigens forms the antigen population, denoted as

$$\mathcal{A}=\left\{\mathbf{p}_1, \ldots, \mathbf{p}_{|\mathcal{A}|}\right\}, \tag{24}$$

where $\mathcal{A}$ is the set to denote the antigen population, and $|\mathcal{A}|$ is the total number of the population set.

• *Concept 2 (Clonal Process)*: To increase the diversity of the antigens, the clonal process generates more antigens to represent the decision variables, according to the clonal rate r_c as:

$$r_c := \left\lfloor \frac{|\mathcal{A}^{\max}|}{|\mathcal{A}|} \right\rfloor, \tag{25}$$

where $|\mathcal{A}^{\max}|$ is the maximum size of the population, and $\lfloor\cdot\rfloor$ is the operation to obtain the floor function.

Using the clonal process, one antigen can be cloned by (r_c-1) additional antigens, forming the clonal population as

$$\mathcal{A}_c=\left\{\mathbf{p}_1^1, \ldots, \mathbf{p}_1^{r_c-1}, \ldots, \mathbf{p}_{|\mathcal{A}|}^1, \ldots, \mathbf{p}_{|\mathcal{A}|}^{r_c-1}\right\}, \tag{26}$$

where $\mathcal{A}_c$ is the set to denote the clonal population. Through the clonal process, the population of antigens increases to $\mathcal{A}^{\max}=\mathcal{A}_c \cup \mathcal{A}$.

• *Concept 3 (Pareto Dominance)*: For all $f(p_a) \in \mathbf{f}(\mathbf{p}_a)$, $f(p_b) \in \mathbf{f}(\mathbf{p}_b)$, if $f(p_a) \le f(p_b)$ and it has at least one strict inequality, we have $\mathbf{f}(\mathbf{p}_a)$ dominates $\mathbf{f}(\mathbf{p}_b)$ within the feasible space of a decision variable $\left[\underline{\mathbf{p}}, \overline{\mathbf{p}}\right]$, in which $\mathbf{f}(\mathbf{p}_b)$ is defined as the dominated antibody.

• *Concept 4 (Pareto Optimality)*: If the objective function of a decision variable dominates the objective function of any other decision variable, this decision variable is defined as the Pareto optimality, denoted as $\mathbf{p}^*$.

The proposed algorithm is implemented to solve the optimisation problems of both the DSO and multiple microgrid traders over the horizon $|\mathcal{T}|$. First, antigens are generated from the feasible space to represent potential values of decision variables. Second, each antigen is cloned to improve the diversity and cover more potential solutions. Third, the dominated antigens and antibodies are removed in every literation, denoted as ι_{F} and ι_{L} for the leader and followers, respectively, so as to remain the non-dominated antigens and antibodies. Fourth, until the maximum number of the iteration, denoted as $\iota_{\mathrm{L}}^{\max}$ and $\iota_{\mathrm{F}}^{\max}$ for the leader and followers, respectively, is reached, the remaining non-dominated antibodies become the Pareto optimality. The details the developed algorithm is presented in **Algorithm 1**.

IV. Case Studies

To demonstrate the effectiveness of the designed framework, case studies were performed using the modified IEEE 69-bus distribution system as presented in Fig. 5. The system was separated into 6 microgrids. 15 solar photovoltaics and 6 dispatchable generators are arbitrarily allocated to 69 buses. Each bus is taken as a load and equipped with a storage devices and an electric vehicle.

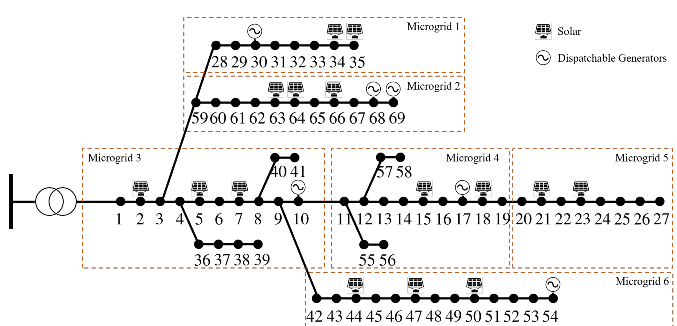

Fig. 5. Modified IEEE 69-bus distribution system. The system is separated into 6 microgrids. 15 solar photovoltaics and 6 dispatchable generators are arbitrarily allocated to 69 buses. Each bus is taken as a load and equipped with a storage devices and an electric vehicle.

Algorithm 1 Solution algorithm to the Stackelberg game-theoretic problem

Input: predicted generation and consumption for all microgrids
randomly initialise the population of antigens from the leader's decision variable space $\left[\underline{\mathbf{p}}_{\mathrm{L}}, \overline{\mathbf{p}}_{\mathrm{L}}\right]$ as $\mathcal{A}_{\mathrm{L}}(0) = \left\{\mathbf{p}_{\mathrm{L},1}, \ldots, \mathbf{p}_{\mathrm{L},|\mathcal{A}_{\mathrm{L}}|}\right\}$
while $\iota_{\mathrm{L}} \leq \iota_{\mathrm{L}}^{\max}$ **do**
  implement the clonal operation as (26), to increase the population of antigens from $|\mathcal{A}_{\mathrm{L}}(\iota_{\mathrm{L}})|$ to $|\mathcal{A}_{\mathrm{L}}^{\max}|$
  remove dominated antigens and antibodies from the population
  while $|\mathcal{A}_{\mathrm{L}}(\iota_{\mathrm{L}})| > |\mathcal{A}_{\mathrm{L}}|$ **do**
    remove antigens and antibodies with the smallest avidities as [36]
  end while
  $\mathcal{A}_{\mathrm{L}}(\iota_{\mathrm{L}}+1) = \mathcal{A}_{\mathrm{L}}(\iota_{\mathrm{L}}), \iota_{\mathrm{L}} = \iota_{\mathrm{L}}+1$
end while
yield optimal solution $\mathbf{p}_{\mathrm{L}}^{\star}$ as the input of followers' optimisation problems
randomly initialise the population of antigens from a follower's decision variable space $\left[\underline{\mathbf{p}}_{\mathrm{F}}, \overline{\mathbf{p}}_{\mathrm{F}}\right]$ as $\mathcal{A}_{\mathrm{F}}(0) = \left\{\mathbf{p}_{\mathrm{F},1}, \ldots, \mathbf{p}_{\mathrm{F},|\mathcal{A}_{\mathrm{F}}|}\right\}$
while $\iota_{\mathrm{F}} \leq \iota_{\mathrm{F}}^{\max}$ **do**
  implement the clonal operation as (26), to increase the population of antigens from $|\mathcal{A}_{\mathrm{F}}(\iota_{\mathrm{F}})|$ to $|\mathcal{A}_{\mathrm{F}}^{\max}|$
  remove dominated antigens and antibodies from the population
  while $|\mathcal{A}_{\mathrm{F}}(\iota_{\mathrm{F}})| > |\mathcal{A}_{\mathrm{F}}|$ **do**
    remove antigens and antibodies with the smallest avidities as [36]
    $\mathcal{A}_{\mathrm{F}}(\iota_{\mathrm{F}}+1) = \mathcal{A}_{\mathrm{F}}(\iota_{\mathrm{F}}), \iota_{\mathrm{F}} = \iota_{\mathrm{F}}+1$
    optimal solution $\mathbf{p}_{\mathrm{F}}^{\star}$
  end while
end while
while the supply or demand of microgrid traders is not matched **do**
  adjust selling or buying price by Eq. (19)
end while
Output: aggregated surplus supply or demand $\sum_{m\in\mathcal{M}} p_{\mathrm{NET},m,t}^{\star}$ and imbalance price $\pi_{\mathrm{DSSP},t}^{\star}$ or $\pi_{\mathrm{DSBP},t}^{\star}$

The profile of energy consumption was sourced from the residential consumers in England. The profile of solar generation was sourced from Renewables.ninja [37] with the installed capacity of 1.5kW for each prosumer. The cost coefficients of the dispatchable generator, vehicle-to-grid, and demand side management are provided in TABLE I. Other parameters were set as $p_{\mathrm{DG},n}^{\max}$=0.5kW, $p_{\mathrm{EV},n}^{\max}$=0.5kW, $\Delta p_{\mathrm{S}}^{\max}$=0.2kW, $e_{\mathrm{S}}^{\max}$=2.5 kWh, and ε=0.003. The simulations were programmed by the Matlab and performed on a computer with Intel(R) Core(TM) i7-4770HQ CPU at 2.20 GHz.

A. Local Energy Balance

The aggregated inflexible power from the solar generation, flexible power from the dispatchable generators, electric vehicles, storage systems, and demand side management and consumption for each microgrid is presented in Fig. 6. It can be seen that the flexible power accounts for a majority portion of the energy self-sufficiency for each microgrid, compared to the solar generation. The microgrid 2, microgrid 4 and microgrid 5 can not only meet the demand of its own prosumers, but also export the surplus energy to other microgrids or utility grids. The negative flexible power is caused when the sum of power charged to the storage systems and load shifting to this time period is greater than the sum of dispatchable generation, power discharged from the storage systems, power-to-grid of electric vehicles, load shifting away from this time period, and load curtailment.

Fig. 7 shows the aggregated net power of the distribution network and imbalance price. The SSP is proportional to the total net supply of the distribution network and SBP is proportional to the total net demand of the distribution network. The net supply can be exported to the utility grids or curtailed. The net demand is satisfied by importing power from the utility grids.

B. Transactive Energy Among Microgrids

The process of multiple microgrid traders cooperatively trade energy with each other during the second scheduling interval is presented in Fig. 8. During this time interval, the

TABLE I
COST COEFFICIENTS OF THE DISPATCHABLE GENERATOR, VEHICLE-TO-GRID, AND DEMAND SIDE MANAGEMENT

	Dispatchable Generators	Vehicle-to-Grid	Demand Side Management
α (£/kWh^2)	7.0×10^{-3}	5.5×10^{-3}	2.8×10^{-3}
β (£/kWh)	1.8×10^{-3}	1.6×10^{-3}	1.6×10^{-3}
γ (£/h)	0.1×10^{-4}	0.2×10^{-4}	0.3×10^{-4}

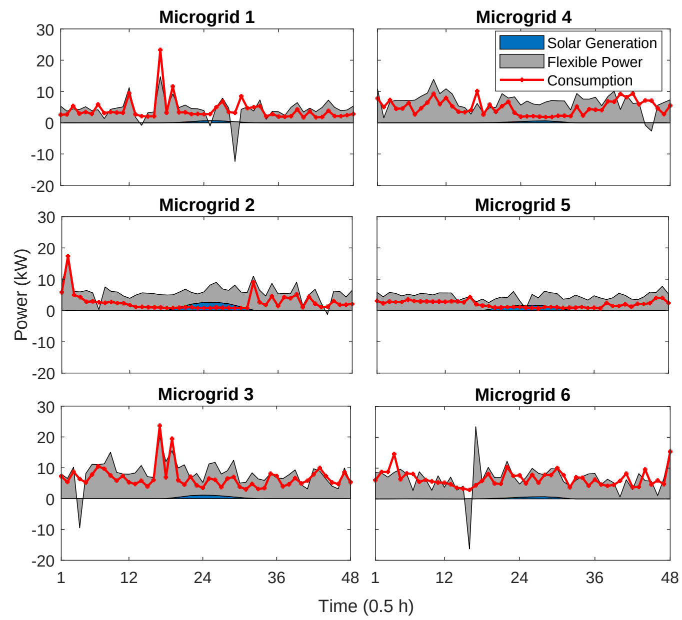

Fig. 6. The aggregated solar generation, flexible power, and consumption of all prosumers for each microgrid. The x axes indicate the scheduling time. The y axes indicate the power.

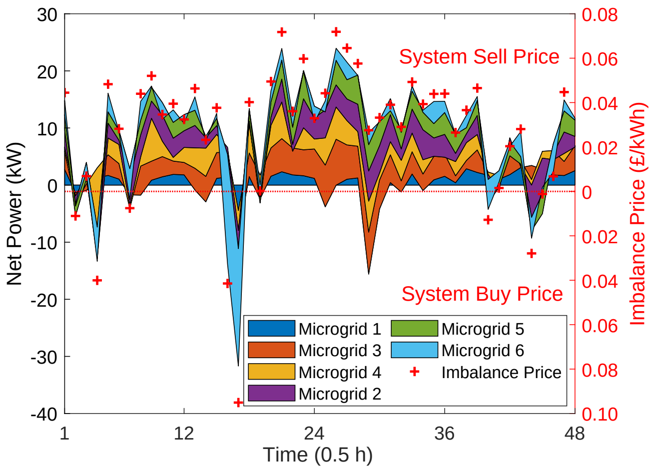

Fig. 7. The aggregated net power of the distribution network and imbalance price. The x-axis indicates the scheduling time. The positive value of left y-axis indicates the surplus supply and negative value of left y-axis indicates the surplus demand. The positive value of right y-axis indicates the system sell price and negative value of right y-axis indicates the system buy price.

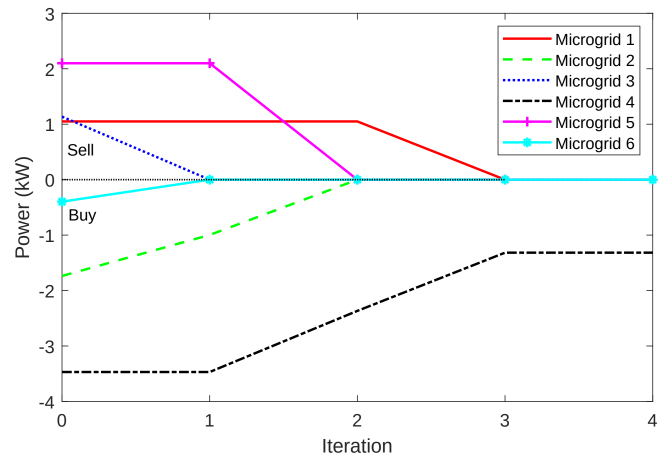

Fig. 8. Unmatched power supply or demand for the transactive energy among microgrid traders. The x-axis indicates the number of iteration. The y-axis indicates the unmatched power supply or demand.

microgrid 1, microgrid 3, and microgrid 5 become sellers, with the selling amount of 1.04 kW, 1.14 kW, and 2.10 kW, respectively. The microgrid 2, microgrid 4, and microgrid 6 become buyers, with the buying amount of 1.74 kW, 3.47 kW, and 0.40 kW, respectively. Since the total demand of buyers is higher than the total supply of sellers, when the unmatched supply is cleared, the negotiation among microgrid traders completes. It can be seen that the negotiation during this scheduling interval converges within 3 iterations. The initial trading volumes and prices are obtained by solving the optimisation problem of each microgrid. At the first iteration, the buyers (microgrid 2 and microgrid 6) buy the power from the microgrid 3 at the agreed price of £0.056/kWh. The supply of the microgrid 3 and demand of the microgrid 6 are cleared. At the second iteration, the buyers (microgrid 2 and microgrid 4) buy the power from the microgrid 5 at the agreed price of £0.069/kWh. The supply of the microgrid 5 and demand of the microgrid 2 are cleared. At the third iteration, 1.05 kW of demand of the microgrid 4 is further satisfied by the supply of the microgrid 1 at the agreed price of £0.0642/kWh. The supply of the microgrid 1 is cleared. The rest unmatched 1.32 kW of demand of the microgrid 4 is imported from the utility grid at the SBP.

C. Performance Evaluation

To evaluate the performance of the proposed model in terms of achieving the local energy balance, the following two models are used as the comparison:

- *Comparison 1 (The Model Without Flexibility Provision):* In this model, prosumers are only equipped with solar panels as the inflexible generation source, without the flexibility provided by dispatchable generators, storage devices, electric vehicles, and flexible loads. Other settings are remained the same as the proposed model.
- *Comparison 2 (The Model Without Transactive Energy):* In this model, prosumers are unable to participate in the transactive energy to exchange surplus supply or demand with each other. The only option is to import or export energy from or to the utility grids. Other settings are remained the same as the proposed model.

The comparison of the net power of the distribution network under these three models is presented in Fig. 9. Compared to the model without the flexibility provision, our proposed model can not only reduce the dependence on the utility grids, but also export surplus power, whereas the model without the flexibility provision has to rely on the power import from the utility grids during the entire scheduling horizon. Compared to the model without the transactive energy in which prosumers can only import energy at the SBP higher than the price determined by the transactive energy, and export energy at the SSP lower than the price determined by the transactive energy, our proposed model can achieve a better local energy balance during the entire scheduling horizon. Incentivised by the prices determined by the transactive energy, prosumers are willing to increase the amount of flexibility provision during the peak demand period from thirteenth to thirty-third scheduling intervals, whereas decrease the amount of flexibility provision during the rest scheduling intervals.

V. Conclusion

This paper proposed a framework of local energy markets to accommodate the emerging role of prosumers and their DRESs. An ensemble of prosumers is structured in the form of microgrids to collectively exchange energy with other microgrids and provide flexibility to the utility grids. The decision making and interactions between the DSO and multiple microgrid traders are analysed using a Stackelberg game-theoretic approach, by which a DSO seeks for local energy balance by scheduling the operation of microgrids and determining the imbalance prices, and multiple microgrid traders seek for maximising the profits of their prosumers through dispatching the flexibility sources and participating in the transactive energy. Case studies show that the proposed model is capable of achieving a better local energy balance

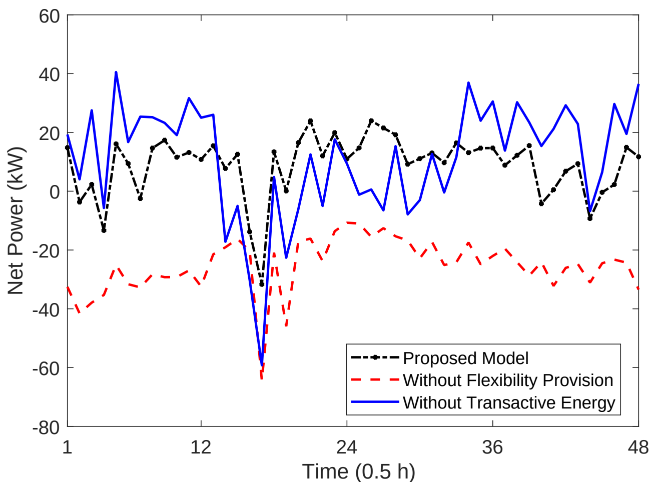

Fig. 9. Comparison of the net power of the distribution network for the proposed model, the model without flexibility provision, and the model without transactive energy. The x-axis indicates the scheduling time. The y-axis indicates the net power.

and reducing the dependency on the utility grids. For future work, the responsibilities of microgrid traders and prosumers, e.g., the cost of using distribution networks, can be evaluated from the regulatory perspective.

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